Chapter

Pre-Harvest and Post-Harvest Techniques for Plant Disease Detections

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Abstract

As the agriculture industry is growing fast, many efforts are introduced to ensure a high quality of produce. Diseases and defects found in plants and crops affect greatly the agriculture industry. Hence, many techniques and technologies have been developed to help solve or reduce the impact of plant diseases. Imagining analysis tools and gas sensors are becoming more frequently integrated into smart systems for plant disease detection. Many disease detection systems incorporate imaging analysis tools and VOC (Volatile Organic Compound) profiling techniques to detect early symptoms of diseases and defects of plants, fruits, and vegetative produce. These disease detection techniques can be further categorized into two main groups: preharvest disease detection and postharvest disease detection techniques. This paper aims to introduce the available disease detection techniques and to compare them with the latest innovative smart systems that feature visible imaging, hyperspectral imaging, and VOC profiling. In addition, this paper considers the efforts to automate imaging techniques to help accelerate the disease detection process. Different approaches are analyzed and compared in terms of work environment, automation, implementation, and accuracy of disease identification along with the future evolution perspective in this field.

Keywords: preharvest, postharvest, disease detection, plants, fruits

1. Introduction

The agriculture industry is undoubtedly one of the most vital sectors contributing to the national income of many developing countries. Throughout the years, many agriculture components and processes have become automated to ensure faster production and to ensure products of the highest quality standards. Because of the increased demand in the agricultural industry, agricultural produce must be cultivated using an efficient process [1]. Diseases and defects found in plants and crops have a great impact on production in the agriculture industry and can lead to significant economic losses [2]. A loss of an estimated 33 billion dollars every year was the result of plant pathogens found in crops in the United States. Pathogenic species affect plants significantly, introducing diseases such as chestnut blight fungus and huanglongbing citrus greening disease [3]. Insect infestation along with bacterial, fungal, and viral infections are other main contributors to diseases found in plants [4]. Changes in climate and temperature are also factors that may contribute to the increase in diseases found in plants. Once a plant has been infected, symptoms develop on various segments of the plant, ultimately degrading the growth of the subsequent fruit or vegetable [5].

Apple production is a huge industry especially in China with over 17 million tons of produce every year. Apple infections do not only significantly reduce grade and yield, but can also affect the return bloom of the following season [6]. These infections have drastic impacts on countries that rely heavily on their agriculture sector as their main source of income. In order to overcome these losses and issues of plant diseases, farmers tend to use chemical pesticides as a remedy solution. This solution may be effective in eliminating plant diseases but has drastic drawbacks. As well as being costly, the increased use of pesticides creates dangerous toxic residue levels on agricultural produce [7]. Not only does the toxic residue affect the healthiness of agricultural produce, but also has a significant impact on the surrounding environment seeping through the soil and into groundwater. This leads to concerns raised by the public about the wholesomeness and healthiness of products when pesticides are commonly used in the produce they purchase [8]. Therefore, the use of pesticides must be controlled and used only when necessary. This controlled or monitored method of pesticide use is known as selective pesticide spraying.

Many techniques have been introduced in order to decrease losses found in defective plants. Manual techniques, such as hand inspection and naked eye observation are very common methods used by farmers. Plant diseases are detected and characterized by observation from experts, which can be very expensive and time-consuming [2]. Because these methods are very tedious it is prone to sorting errors and judgmental errors from different farmers [6]. Therefore, different disease detection systems were introduced to tackle many of the issues faced with labor-intensive techniques.

A disease detection system has the ability to not only detect early symptoms of defective plants but can also prevent the disease from spreading. Disease detection techniques can be categorized into two methods: direct and indirect methods [4] as shown in **Figure 1**. Direct detection techniques rely on the use of laboratory-based experiments. The most popular and commonly used experiments are enzyme-linked immunosorbent assay (ELISA) and polymerase chain reaction (PCR) [4]. Indirect methods rely on advanced techniques that are mainly focused on field-based approaches. Indirect methods emphasize the integration of sensors and imaging techniques on-site, to provide a rapid and accurate method for disease detection. Early detection of apparent diseases in plants is of utmost importance [1], as this will aid farmers to take appropriate precautions to help preserve the defective plant. Indirect methods are vast and can be used for disease detection in both preharvest plants and post-harvest produce. If early detection is possible, the percent of defective fruits can be significantly decreased, while maintaining high-quality production standards.

1.1 Direct methods

When a pathogen attacks a plant, the plant DNA is altered, and a specific type of protein molecules are introduced to the plant by the pathogen during infection [9]. Direct methods focus on molecular and serological techniques that test the biological structure of the plant to check for the pathogen DNA or the presence of pathogen produced protein molecules. Commonly known techniques are the Polymerase chain reaction (PCR) and the Enzyme-linked immunosorbent assay (ELISA). PCR-based disease detection involves genetic material (DNA) extraction of the microorganism causing the disease. The gel electrophoresis is then performed after the DNA has been purified and amplified. If a specific band is present in the gel

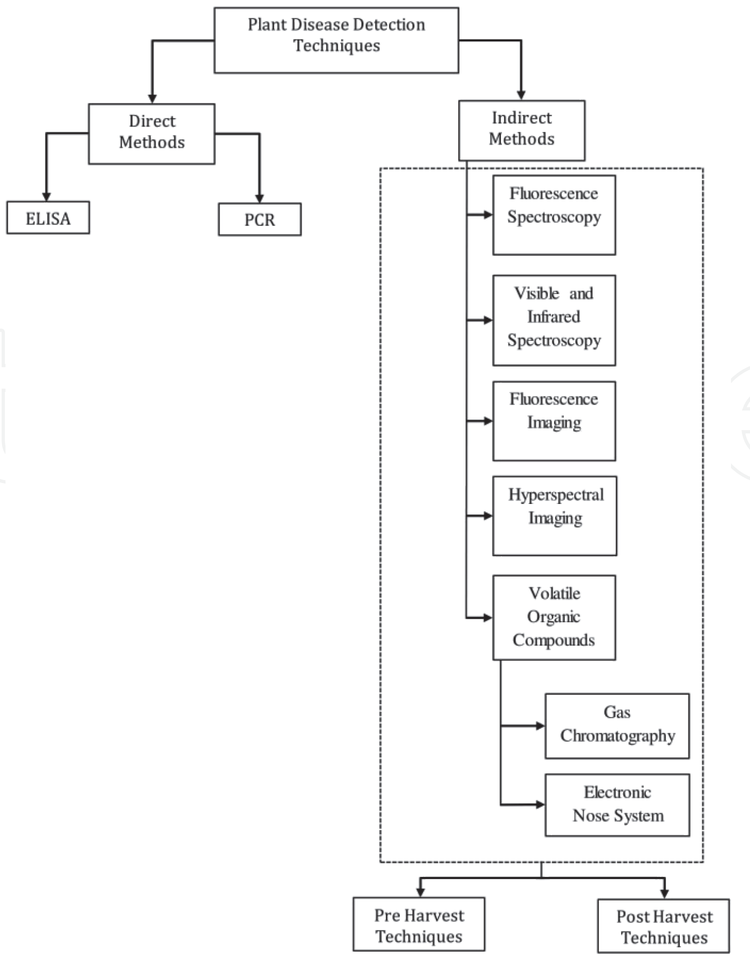


Figure 1.
Different methods of plant disease detection.

electrophoresis, then the existence of the plant disease organism is verified [4]. ELISA works by injecting the microbial protein of a specific plant disease into an animal, which in return produces antibodies against that specific disease. The extracted antibodies are used alongside fluorescence dye and enzymes for disease detection. If the plants were infected, then the sample would fluoresce, verifying the presence of a particular plant disease [4]. **Table 1** illustrates the difference between each technique and how they compare in disease detection. Because of these techniques, diagnostic kits have been designed to successfully detect diseases in crops such as rice and can also identify genetically modified organisms (GMOs) in shipments of conventional crops.

Although these techniques may be robust and very accurate in detecting plant diseases, the drawbacks of these methods are significantly vast. These techniques rely heavily on the use of expensive laboratory equipment and extensive experiments, which can be time-consuming and labor-intensive. Sample preparation

	ELISA	**PCR**
Diagnostic Kit	Protein-based	DNA-based
Cost	Simple laboratory equipment with no training required	Expensive costly equipment
Disease Detection	Root crops, fruits, and grains	Bananas, potatoes, and cotton

Table 1.
A comparison between ELISA and PCR techniques for plant disease detection.

consumes a considerable amount of time and effort to ensure reliable and accurate results. These techniques are also very expensive because of the use of consumable reagents that are specifically designed for each pathogen [4]. Therefore, new and more rapid disease detection systems are needed as a preliminary screening tool for processing large numbers of plant samples.

1.2 Indirect methods

New automated non-destructive methods have been studied to detect plant disease symptoms early and with high sensitivity to specific diseases. The most common techniques used are spectroscopic and imaging techniques for the detection of symptomatic and asymptomatic plant diseases [4]. The methods studied include fluorescence spectroscopy, visible and infrared spectroscopy, fluorescence imaging, hyperspectral imaging, and VOC profiling.

Fluorescence spectroscopy works by exciting an object with a beam of light and measuring the fluorescence released. Fluorescence spectroscopy systems can be used in field-based settings where leaves are still attached, and in laboratory settings where sample leaves are detached. Studies have shown that this method is accurate in discriminating defective plants from non-defective plants [10]. However, studies have also shown that this method is inefficient in providing enough information, such as water stress levels [11]. Visible and infrared spectroscopy is a rapid and cost-effective technique that can be used as a plant disease detection system. Studies have proven that this method can be used to detect stress levels and detect plant diseases accurately, even before symptoms are visible [12]. Unlike fluorescence spectroscopy, where only a single spectrum is used, fluorescence imaging works by using images obtained from a camera. Wavelengths from an object are recorded on a camera after fluorescence excitation from a UV light. A study confirmed that this method could be used to detect the tobacco mosaic virus (TMV) in tobacco plants.

Non-infected tobacco plants were successfully differentiated from infected ones in a relatively short period of time [13]. Hyperspectral imaging is similar to multispectral imaging but uses a wider range of wavelengths for each pixel. An image is produced consisting of a set of pixel values at each wavelength of the spectra. This method is common in monitoring the quality of food products, such as fruits. A study developed a system for early detection of yellow rust disease in winter wheat using visible-NIR hyperspectral imaging. Using quadratic discriminant analysis as the classification method yielded an accuracy of 92–98% when classifying diseased plants [14]. VOCs are released by plants due to factors such as humidity, temperature, light, soil condition, and fertilization [15] Studies have shown that certain compounds are released when a plant is under stress or is infected by a particular disease [16].

These methods were proposed to be integrated with an autonomous agricultural vehicle to provide real-time feedback of plant stresses and nutrient deficiencies. Not only have these methods been shown to provide successful detection of plant stress and nutrient deficiencies, but also have been useful in monitoring the quality of postharvest fruits and vegetables.

2. Preharvest disease detection techniques

Indirect methods can be used to detect diseases in both preharvest and postharvest fruits/vegetables. To have a better understanding of different disease detection techniques, indirect techniques can be further categorized into two main groups: preharvest and postharvest detection techniques. This section will include more in-depth research on the use of imaging techniques and VOC detection techniques for disease detection in preharvest fruits/vegetables.

Patil [17] proposed a method in which leaf disease severity of preharvest sugarcane leaves can be measured using imaging techniques. Fungi diseases are very common in sugarcane leaves and inhibit their growth immensely. These diseases leave visual spots on leaves, which in turn prevent the vital process of photosynthesis. Photosynthesis is a fundamental process essential for growth and prosperity. Rather than using pesticides, which is not only costly but also increases toxic residue levels, an early disease detection system can be implemented. Because fungi-caused diseases in sugarcane leaves appear as spots it is applicable to use imaging techniques to detect the severity of the disease [17]. Disease severity is expressed as the ratio between the affected area and the leaf area. If the lesion area to leaf area ratio is high, then the leaf is said to have a high disease severity according to **Table 2**.

For this study, 90 infected sugarcane leaves were used as image samples taken by a 12 Megapixel digital camera. The images were taken in a controlled environment with a white background and light sources to eliminate any reflection and to provide enhanced view and brightness [17]. For improved results, the input leaf image in **Figure 2** is first transformed from RGB color space to HIS color space. The image is then converted to grayscale as shown in **Figure 3** which is then segmented into two regions: the diseased region and the healthy region shown in **Figure 4**.

In order to segment the image, a triangle thresholding method was used. After the image has been segmented the leaf area and infected area ratios are calculated by measuring the number of pixels in the white region and the black region, respectively. This experiment showed to be very successful with an average accuracy of 98.60%.

To further improve the efficiency and accuracy of leaf disease grading systems, Sannakki [7] proposed the use of machine vision and fuzzy logic for disease detection in pomegranate leaves. Similar to the previous research, a table-like

Category	Severity
0	Apparently Infected
1	0–25% Leaf Area Infected
2	26–50% Leaf Area Infected
3	51–75% Leaf Area Infected
4	>75% Leaf Area Infected

Table 2.
Disease severity scale developed by Horsfall and Heuberger [17].

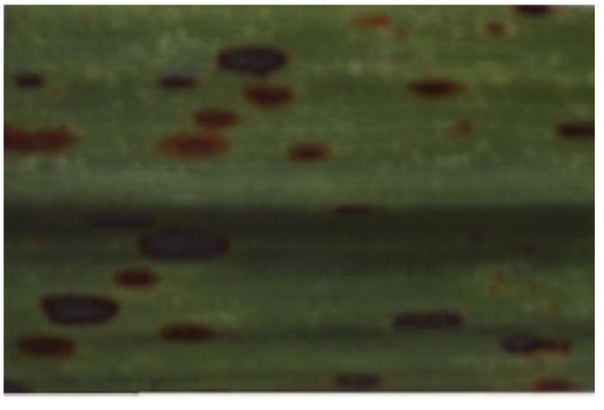


Figure 2.
RGB color space of brown spotted diseased sugarcane leaf [17].

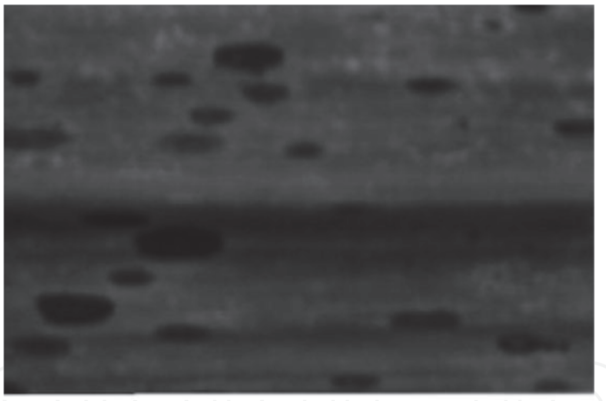


Figure 3.
Grayscale image of brown spotted diseased sugarcane leaf [17].

Figure 4.
Infected region detection after triangle thresholding [17].

percent-infection calculation method is used to illustrate the severity of the disease. A 10 megapixel Nikon Coolpix L20 digital camera was used to take images of disease-infected pomegranate leaves at an equal distance of 16 cm. Images were taken from several pomegranate farms with no specific test site indication. A few image restoration techniques are implemented before the image is segmented into two specific regions: disease region and healthy region. Firstly, to reduce the computational complexity of the system, images are first resized to a fixed resolution. Then by the use of a Gaussian filter any noise or outer interference in the image is removed or diluted. K-means clustering (K = 10) technique is used here as the segmentation method, and the cluster that contains the diseased spots are saved to calculate the area of the diseased region. After calculating the disease area (AD) and total leaf area (AT), it is now possible to calculate the percent of infection in regard to the total area. A fuzzy logic system is implemented in order to characterize which disease grade the disease belongs to depending on the percent infection. It is difficult to assess which disease grade the disease belongs to because of the ambiguity and uncertainty of the table, but a fuzzy logic system can be effective in this case. The segmented regions that are used to calculate the percent-infection index are shown in **Figures 5** and **6**. The fuzzy logic system proved to be very effective in accurately grading diseases into their appropriate categories.

Because it can take up to one week to diagnose plant diseases using traditional chemical analysis, Xu [18] proposed an early plant disease detection technique. During the period of anthesis plants often appear to be nutrient deficient and it is vital to detect these deficiencies early to ensure the quality and quantity of plants. Nutrient deficient plants usually leave quite visible symptoms on their leaves, which can be

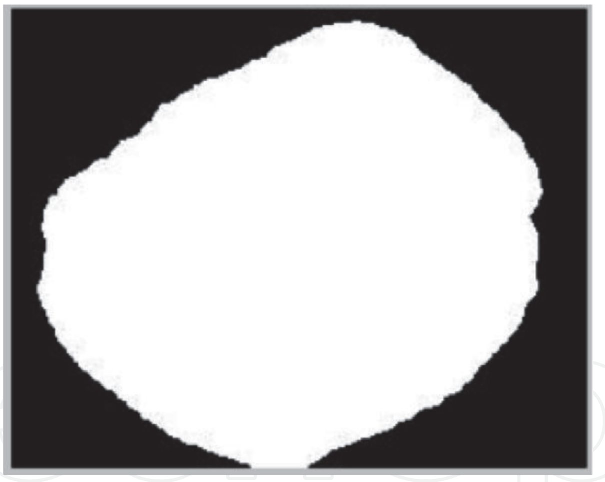


Figure 5.
Total leaf area (AT) of pomegranate leaves shown as a white spot [7].

Figure 6.
Disease area (AD) of a pomegranate leaf shown as white spots [7].

used to diagnose the disease. By extracting features from leaves such as color and texture, plant nutrient deficiency can be diagnosed at an early stage [18].

Nitrogen and potassium deficient tomato plants were used under a controlled chamber environment to extract color and texture features of leaves. A sampling box shown in **Figure 7** was used to take colored images of tomato leaves with a digital camera. Normal, prophase, and anaphase of nitrogen and potassium deficient tomato leaves were used in the proposed system as shown in **Figure 7**.

After images are taken in the chamber they are processed for color and texture feature extraction. Because nitrogen-deficient leaves turn yellow with the development of a disease, the number of yellow pixels in the leaf image can reflect the feature of nitrogen deficiency. Therefore, Xu [19] proposed the use of percent histograms to extract color features. The extracted feature set was classified using a fuzzy K nearest neighbor classifier and proved to be quite accurate in identifying normal, nitrogen deficient, and potassium deficient leaves.

The proposed system was tested using sample collection of tomato leaves and showed to be effective with an accuracy of identifying normal leaves, nitrogen-deficient leaves, and potassium deficient leaves to be 92.5%, 85%, and 82.5% respectively. The diagnostic system can identify potassium deficiency in leaves 10 days earlier than by experts' observation. This gives a significant amount of time for measures to be taken to ensure high-quality production.

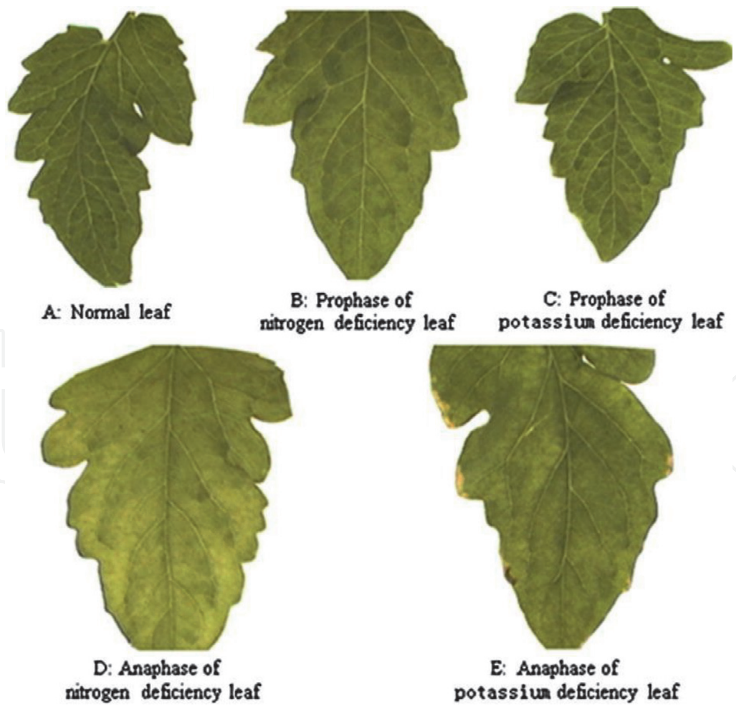


Figure 7.
Examples of images used in the diagnostics system [18].

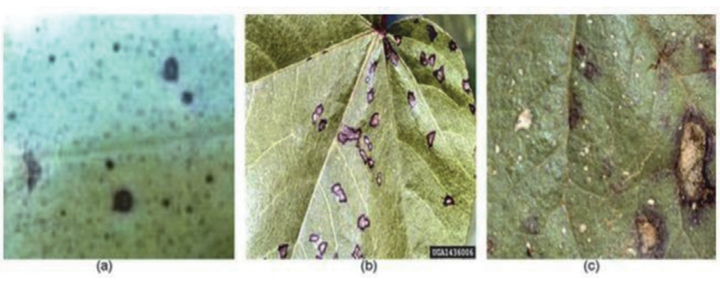


Figure 8.
Image of cotton crops showing the visual symptoms of damages caused by (a) southern green stink but; (b) bacterial angular; (c) Ascochyta blight [20].

In order to help crop producers and farmers in remote areas to identify early symptoms of plant disease, Camargo [20] used image processing and pattern classification to implement a machine vision system. The system would detect cotton crop damage caused by 3 specific diseases: green stink bug, Bacteria angular, and the Ascochyta blight virus as shown in **Figure 8**. A set of 117 images were used in the study from different sections of the plant such as the leaf, fruit, and stem [20]. Multiple features that characterize the shape and appearance of the image were extracted using both the image's RGB and HSV color space. For texture extraction, a co-occurrence matrix was used to identity gray levels between a specific position in the image and its neighboring pixel.

A box-counting algorithm was used to estimate the dimensions of the image for fractal dimension feature extraction. Gliding Box Algorithm was used to calculate the lacunarity feature to measure texture associated with patterns. A Support Vector Machine Classifier was used to identify the best classification model for the different feature sets. Each feature was used individually and grouped to identify the difference in classification accuracy with respect to feature type [20].

Results showed that grouping features of similar type resulted in higher classification accuracies when compared to using individual features. Results also showed that grouped texture features achieved higher classification rates (83%) when compared to grouped shape features which achieved a classification rate of 55%. When using the total feature set the highest classification rate was achieved of 90%. To further enhance the classification accuracy, one feature was withdrawn at a time until the best feature set was discovered. Using this method, a deducted feature set resulted in a classification accuracy rate of 93.1%.

In order to decrease the cost of uniform and periodical pesticide spraying, Oberti [8] suggested a selective spraying solution using an agriculture robot. Because primary infections start from localized discrete foci, a system can be implemented to detect these infected foci points and targeted treatment can be established. Eliminating the initial infection point does not only inhibit the spread rate of the infection to other patches but also significantly decreases the use of pesticides. In this case study, a multispectral camera is used to inspect an entire grapevine canopy for automatic detection of powdery mildew and selective spraying is achieved using a six-degree robotic arm illustrated in **Figure 9**.

The red, green, and NIR channels were the primary channels used for disease detection. An RGB camera was also added to the camera rig for visual documentation of the scene. The cameras were positioned at a constant height of 1.4 m while maintaining a distance of 1 m from the canopy wall as shown in **Figure 10**. Halogen light panels were used to provide diffused illumination of the imaged area for enhanced and more accurate results for indoor conditions. The disease detection algorithm used in this system was to capture very sharp changes in the reflectance in green and red channels, as this will give a clear indication of the breakdown in chlorophyll content in infected leaves. Specifically, two indexes were calculated and used to measure chlorophyll absorption illustrated in Eqs. (1) and (2):

$$I1 = (\text{Red Green}) = \text{NIR}^2 \tag{1}$$

$$I2 = \text{Red} = (\text{Red} + \text{Green} + \text{NIR}) \tag{2}$$

Since healthy regions have high chlorophyll absorption, it is expected that I1 and I2 will yield higher values for diseased areas and return lower values for healthier regions. To test the proposed system, grapevine plants were used to recreate a vineyard canopy wall in a greenhouse as shown in **Figure 11**.

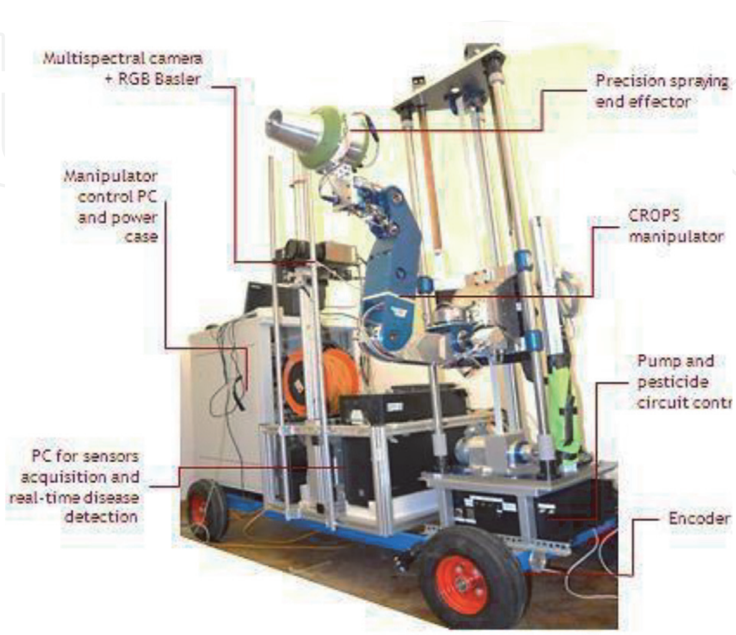


Figure 9.
Robotic vehicle for disease detection and selective pesticide spraying [8].

Figure 10.
Camera setup for the agricultural robot [8].

Figure 11.
Healthy grapevine plants aligned together with infected plants positioned randomly circled in red [8].

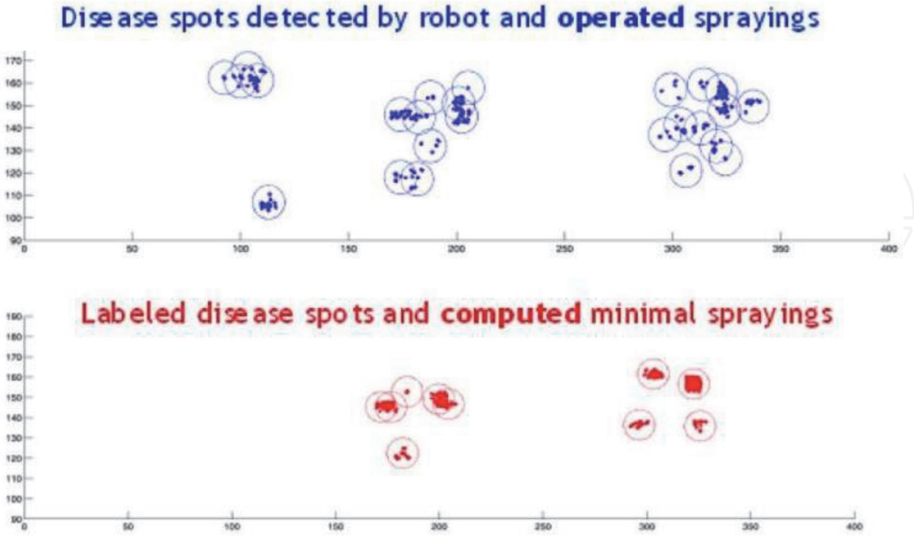


Figure 12.
Disease spots detected by robot and operated sprayings (blue) against labeled disease spots and computed minimal sprayings (red) [8].

Figure 12 illustrates the results gathered after the first experimental run. The blue graph shows the disease spots detected by the robot (blue dots) and the robot sprayings (blue circles) operated by the robot. To analyze the results, the blue spots are compared against the actual disease spots (red dots) specified by a plant pathologist and computed minimal sprayings (red circles). In the first experimental run, the robot detected all the diseased areas and successfully covered all the disease foci with pesticide spraying. The selective pesticide spraying achieved here obtained a reduction in pesticide use up to 84% when compared to homogenous spraying of the canopy. However, at different instances the robot did detect disease spots in areas where plants were healthy, this is apparent around the 100th mark. This false detection can be the result of illumination changes and shadow effects, which distort the input image and hence the values of I1 and I2. Also, the increased operated sprayings around detected diseased areas by the robot is apparent when compared to minimal sprayings. Oberti [8] claims that the surroundings of detected disease areas can be treated anyway by including a conservative safe-border area. This may help to raise the level of acceptance in real-world cases, despite the reduction in potential pesticide savings. Overall, the proposed system proved to detect disease foci with an accuracy of 85%, while achieving a reduction of pesticide use close to 90%.

Pobkrut [21] used a semi-autonomous mobile e-nose robot to examine the fertility of the soil by using metal oxide gas sensors to detect organic volatile compounds found in soil. A six-wheel robot was designed with an integrated array of gas sensors shown in **Table 3**. This e-nose system was used because of its low cost and high sensitivity to certain target gases [21].

Multiple fans were installed on the robot to ensure airflow towards the gas sensor enclosed chamber as shown in **Figure 13**. The data collected from the gas

Sensor	Target gases
TGS 825	Hydrogen sulfide
MQ2	Combustible gases
MQ5	LPG, natural gases
MQ135	NH3, NOx, Benzene, CO_2 gas
TGS 2600	Air contaminants (ethanol, isobutane, hydrogen)
TGS 2602	VOCs and odorous gases

Table 3.
TGS and MQ gas sensors and their target gases [21].

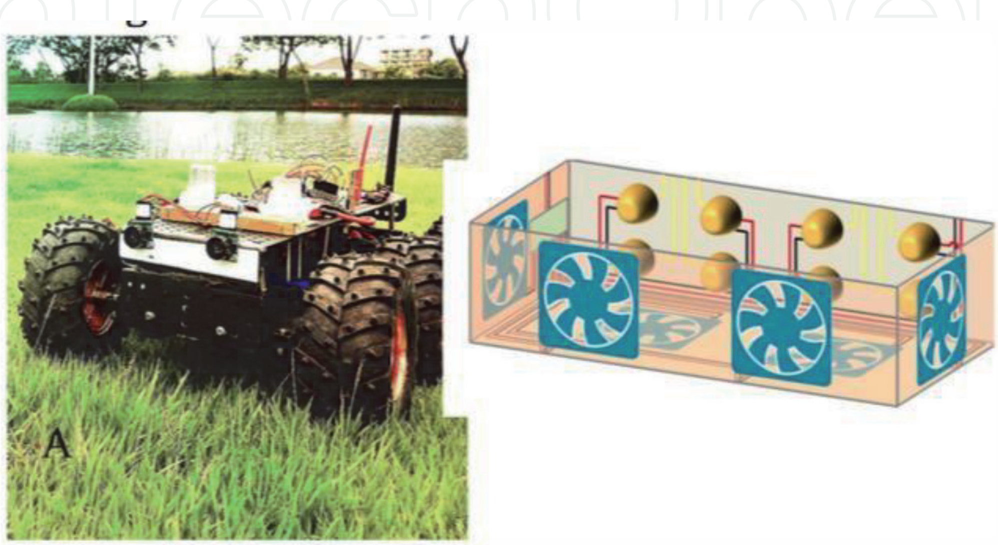


Figure 13.
A six-wheel robot with E-nose and navigation system and an e-nose chamber [21].

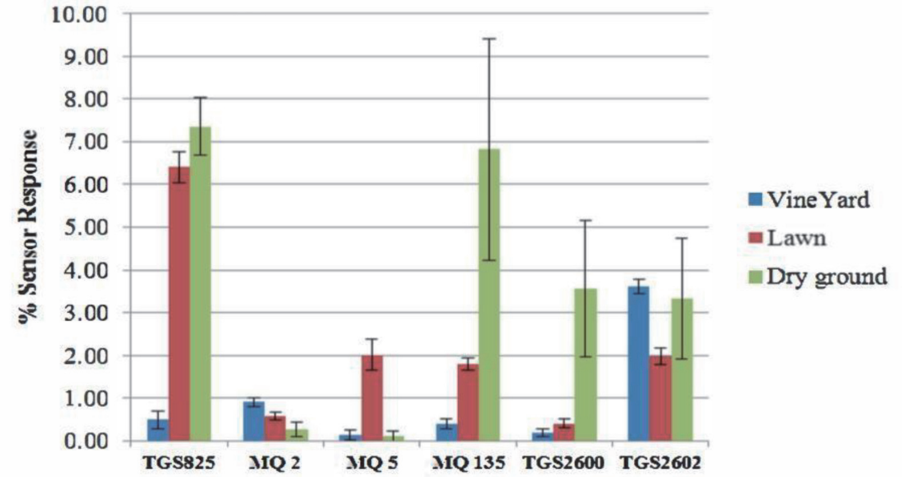


Figure 14.
Percent sensor responses of six elements used in the e-nose robot system to soil volatiles at different places [21].

sensors were recorded in real-time and sent to a computer for analyzing and visualizing via Zigbee wireless network. Ultrasonic sensors and accelerometers were also implemented in the robot to ensure obstacle avoidance and smooth navigation. The robot was operated under real conditions in four different locations, floor room, lawn, dry ground, and vineyard row.

From **Figure 14**, it can be observed that the results collected from the dry ground location yielded a high percentage in sensor response to most of the gas sensors. This can be because little to none of the volatile gases are absorbed from the surroundings because of the lack of weeds and grass [21]. Most gas sensors yielded quite low responses in the vineyard location except for TGS2602, because of its high sensitivity to odorous gases such as ammonia and hydrogen sulfide. TGS2602 also has a high sensitivity to VOCs such as toluene [21]. The six different sensors show promising results in indicating different volatile gases in dry ground. Pobkrut [21] argue that if enough common odor data from various places are collected and put into a database, this database can later be used to determine irregular events.

3. Postharvest disease detection techniques

After reviewing different approaches to plant disease detection in preharvest harvest produce it is necessary to discuss postharvest detection techniques.

The method proposed by Jhuria [1] uses image techniques and artificial neural networks (ANNs) to classify different diseases found in grapes and apples. Image processing was used to extract specific features such as fruit color, texture, and morphology. An important factor that may aid or diminish the effectiveness of image processing is the selection of the color space. Jhuria, Kumar, Borse [1] proposed that the HIS color space is more suitable than RGB as it is less affected by changes in light. A neural network was used to characterize these features into a disease category such as apple scab or apple rot. The neural network was first trained with a data set of various apple diseases. **Figure 15** illustrates the different steps taken during the training and testing of the neural network.

After being trained, the neural network was capable of characterizing an input apple image into its corresponding disease category. It was concluded that the selection of features plays a vital role in the effectiveness of the neural network. Because diseases are better defined by color and morphology, these features, unlike texture, proved to provide improved results [1].

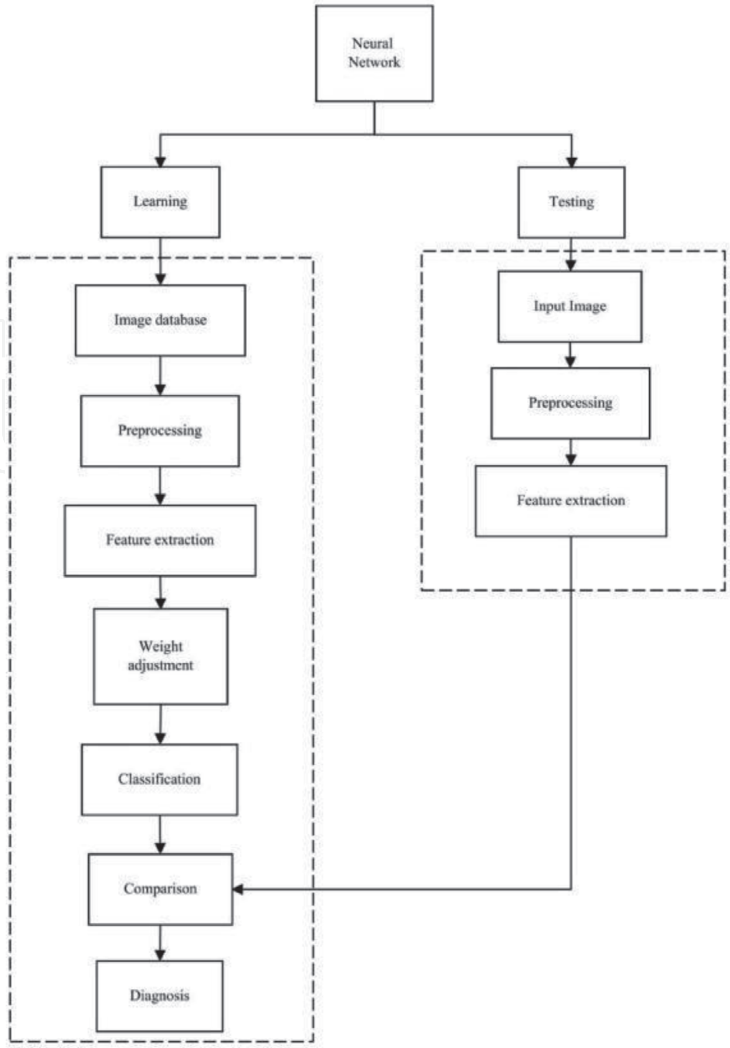


Figure 15.
Flowchart of the proposed system for training the neural network to determine diseases in apples and grapes [7].

Dubey [2] provided a similar technique with the use of a Multi-class SVM (Support Machine Vector) classifier and K-Means image segmentation to detect three diseases found in apples: apple blotch, apple rot, and apple scab. Because of the wide variety of skin colors found in different apples, it was proposed that using size and color as features could be challenging in the detection of defects in apples. Therefore, a K-means based image segmentation approach was used to extract disease features.

In order to ensure shorter processing times for image segmentation, L*a*b* color space was used [2]. K-means clustering was used to segment the apple image into 4 different clusters by categorizing similar pixel densities into their corresponding cluster. Dubey [2] proposed that for improved segmentation results, using 3 to 4 clusters was sufficient. **Figure 16** demonstrates the results of the K-means clustering for apples with different infections.

It is clear that the K-means clustering technique is an effective tool for image segmentation. Four different techniques were used for feature extraction, Global Color Histogram (GCH), Color Coherence Vector (CCV), Local Binary Pattern (LBP), and Complete Local Binary Pattern (CLBP). These color and texture features were used to validate the accuracy and efficiency of the proposed system [6]. GCH represents the probability of a pixel being a certain distinct color in the form of a histogram, whereas the CCV distinguishes coherent and incoherent pixels into two separate histograms. Coherent pixels are defined as pixels that belong to a large region with homogenous color, and any other pixel is defined as an incoherent

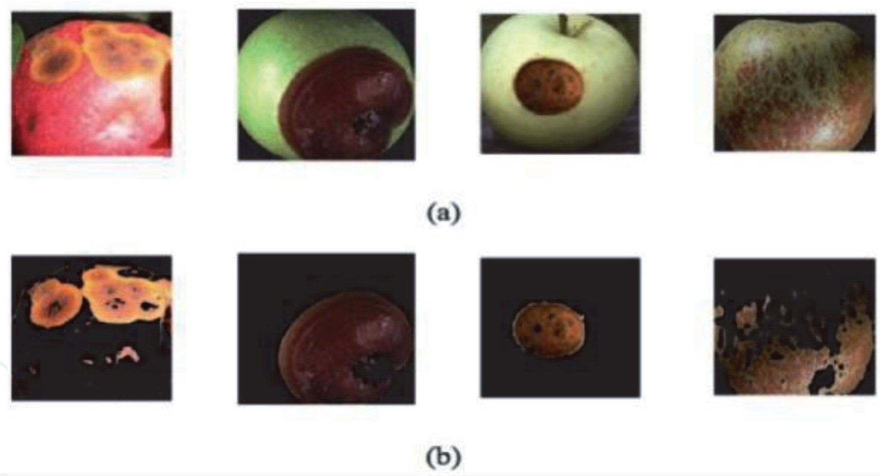


Figure 16.
Image results before (a) and after (b) K-means clustering segmentation [2].

pixel. LBP considers the difference of each pixel with respect to its neighbors. CLBP on the other hand, considers signs, magnitude, and original center gray level value of local differences. After the extraction of features, a Multi-class Support Vector Machine (MSVM) was used for the training and classification as shown in **Figure 17**.

Support Vector Machines have significant advantages over ANNs as they are less prone to overfitting and require less computational power. However, since ANNs use a heuristic method, it is easier to develop than an SVM, which involves more theory. A data set of 431 apple images was created with wide variations in apple type and color to ensure a more realistic test [2]. The data set is to be categorized into Apple Botch, Apple Rot, Apple Scab, or Normal Apple categories.

Results proved to coincide with Jhuria's [1] proposal that the use of HSV color space outperforms RGB color space [2]. It is clear from **Figure 18** that using the HSV color space in every feature extraction technique yields more accurate results. Also, **Figure 18** shows that the most accurate extraction techniques are the CLBP

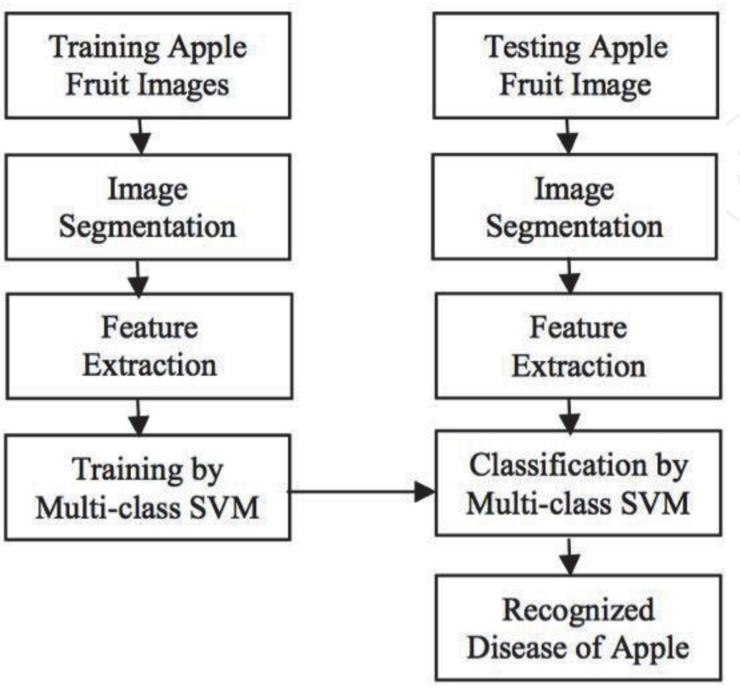
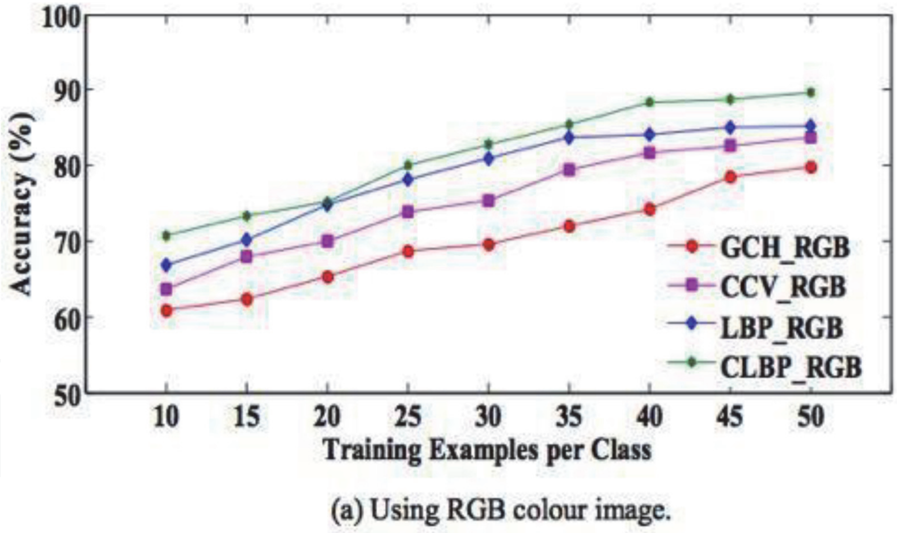


Figure 17.
Flowchart of the proposed MSVM system [2].



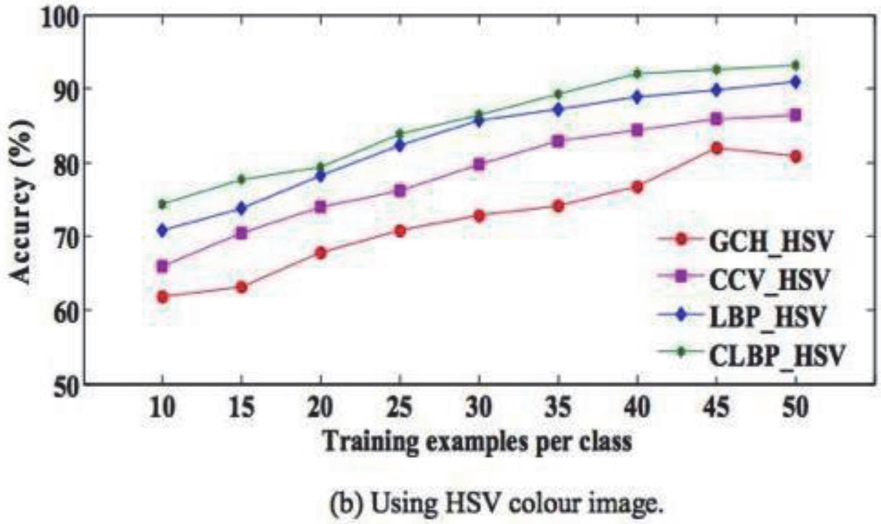


Figure 18.
Accuracy difference of using RGB color space compared to HSV [2].

followed by the LBP. Unlike GCH and CCV, both CLBP and LBP use information from neighboring pixels. Because they use local differences, they are more efficient in pattern matching and are less computationally extensive. It can be concluded that it is more effective to use either LBP or CLBP as feature extraction techniques to yield more accurate results. Furthermore, results indicated that the MSVM classifier detection of normal apples and apple scab was significantly easier than the detection of apple blotch and apple rot. **Figure 19** illustrates this observation, with very high accuracy results for the detection of normal apples and apple scab by using the LBP technique. However, the accuracy rates for the detection of apple blotch and apple rot are significantly lower.

To increase the speed of the sorting process, Unay [22] suggested a computer vision-based system to automatically grade apples. A monochrome digital camera with multiple band-pass filters was used to capture one-view images of 'Jonagold' apples taken in a controlled illuminated environment. The data set consisted of 280 healthy apples and 246 apples included several skin defects such as bruises and rot. The four bandpass filters used for image acquisition are centered at 450 nm (Blue), 500 nm (Green), 750 nm (Red), 800 nm (Infrared) as shown in **Figure 20**. Images of apples were taken in a uniform and low-intensity background to ensure a controlled environment. Therefore, background segmentation can be easily achieved

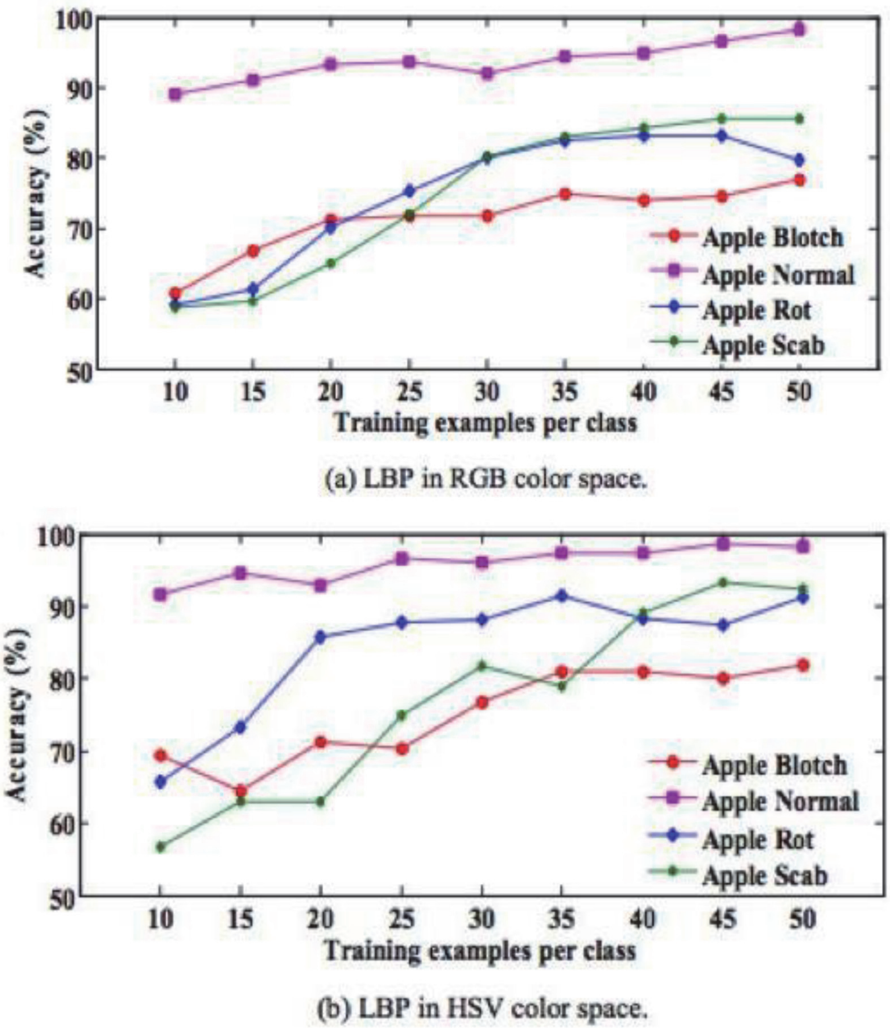


Figure 19.
Accuracy of detecting different apple disease categories in RGB and HSV color space [2].

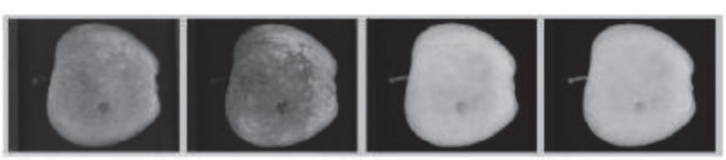


Figure 20.
Filter images of apple. Left to right: Blue, green, red, infra-red filters [22].

using a thresholding technique. Multiple global thresholding techniques such as Otsu, Entropy, and Isodata were tested for defect segmentation. However, because of the similar appearance of the stem-end/calyx area and the apple defect, a segmentation technique is required to distinguish them from one another. Stem-end and calyx are natural parts of the apple and usually appear as dark blobs which can be often mistaken as defects. Statistical, textural, and shape features are extracted and introduced to a support vector machine to distinguish the calyx from the defect. The result of this segmentation can be seen in **Figure 21**.

After calyx removal, a total of 13 features were extracted and introduced to multiple fruit classification techniques to test the accuracy of different classifiers. The 5 classifiers used were Linear Discriminant Classifier (LDC), Nearest Neighbor (k-NN), Fuzzy Nearest Neighbor (fuzzy k-NN), Adaptive Boosting (AdaBoost), and Support Vector Machine (SVM).

Figure 22 illustrates the different thresholding techniques with all 4 filters. It is quite apparent that unlike the blue and green filters, the red and infrared images

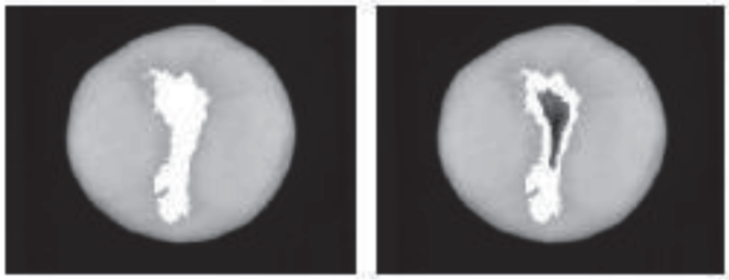


Figure 21.
Example of stem-end/calyx removal. Before the removal on the left and stem-end/calyx removed on the right. Defected areas displayed in white in both images [22].

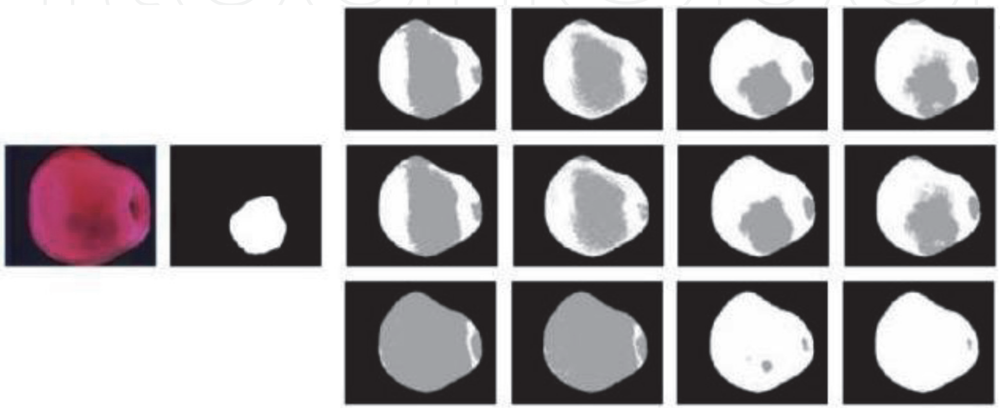


Figure 22.
Segmentation results of thresholding methods on a bruised apple. Original RGB image and the manual segmentation of the fruit are on the left. Subsequent synthetic images show defected regions in gray and healthy ones in white. Each row belongs to a thresholding method (top-to-bottom: Otsu, isodata, entropy) and each column shows a band (left-to-right: Bl, GR, RE, IR) [22].

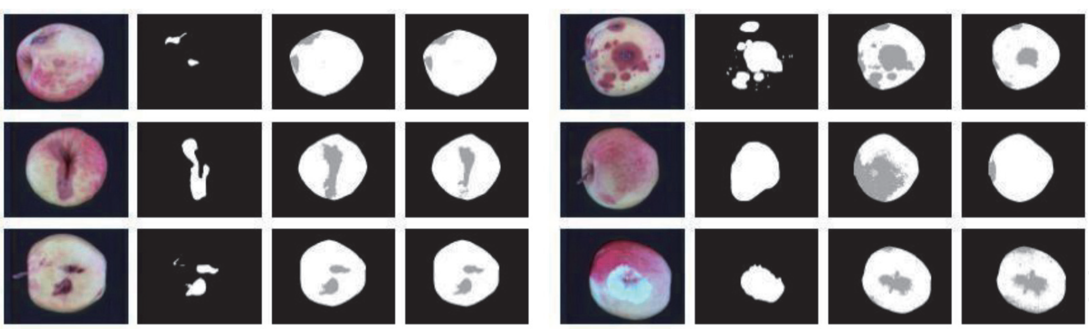


Figure 23.
Results of segmentation by isodata thresholding on RE and IR filter images. Fruits displayed are defected by scald (top-left), rot (top-right), frost damage (mid-left), bruise (mid-right), hail damage perfusion (bottom-left) and flesh damage (bottom-right). For each fruit, its original RGB image, its manual segmentation, and its segmentation results are displayed in a row. Defected areas are displayed in white in manual segmentation image, whereas segmentations show defected regions in gray color and healthy ones in white [22].

provide a more accurate representation of the defect segmentation. Blue and green filter images result in false segmentation because of the low contrast between healthy and defective skin in the wavelength range of 410-510 nm. **Figure 22** also shows that isodata thresholding accurately segments the defective area when compared to Otsu and entropy thresholding.

To further validate the results more apple images were segmented using the Isodata thresholding technique on Red and Infrared filters. **Figure 23** shows that results of Red filter images give better segmentation results when compared to Infrared filter images. After calyx removal, defect segmentation, and feature extraction, apples are graded by different classifiers as mentioned before. SVM proved to be the most accurate classifier (89.2%) in this case when using the Isodata method with the Red filter images. The LDC and k-NN classifiers performed lower with accuracies of 79% and 83% respectively.

Li [6] proposed a more automated approach using an on-line experimental system that can simultaneously inspect all four sides of an apple, and sort them accordingly. Two main issues with previous studies were tackled; the first is to acquire the whole surface of an apple at on-line speeds and to quickly identify the apple stem and calyx. A description of the system schematic is represented in **Figure 24**. The schematic displays how apples are fed into the machine vision system via conveyors and belts for image acquisition, and how they are sorted accordingly. The feeding conveyor is designed to ensure that the stem of the apple is faced upwards for maximum performance. The machine vision system consists of two cameras to provide multiple images of the apple, and a lighting chamber to control the light distribution [6]. By use of mirrors the top camera will cover three side views of the apple: top and two sides. The camera below will take an image of the bottom view of the apple. This setup has the distinctive advantage of inspecting all sides of the apple in one cycle. The setup is illustrated further in **Figure 25**.

After image acquisition, multiple methods were implemented for accurate defect detection. To not disrupt the segmentation process, image background removal algorithms were implemented to ensure that any backgrounds such as the mirror are removed. Segmentation is completed by using a reference fruit image and then subtracting it from the original fruit image. Then by the use of a simple thresholding method the defects could be easily extracted [6]. Because stem and calyx defects are very similar to each other the authors proposed the use of neural networks to distinguish the stem and calyx defects.

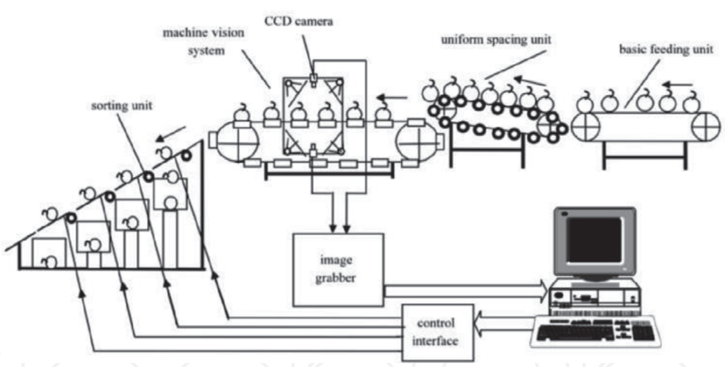


Figure 24.
Schematic representation of apple defects sorting system [6].

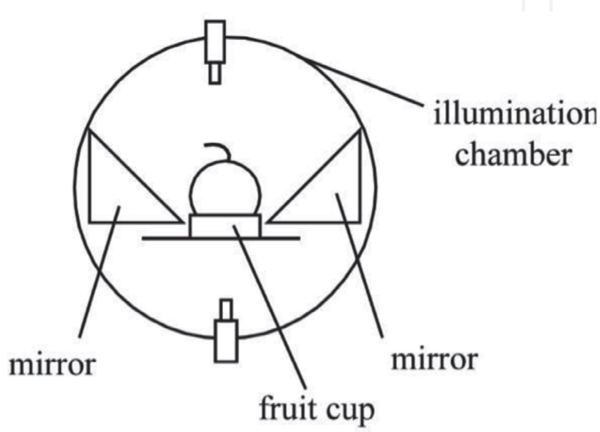


Figure 25.
Setup of the mirror vision system on the sorting system [6].

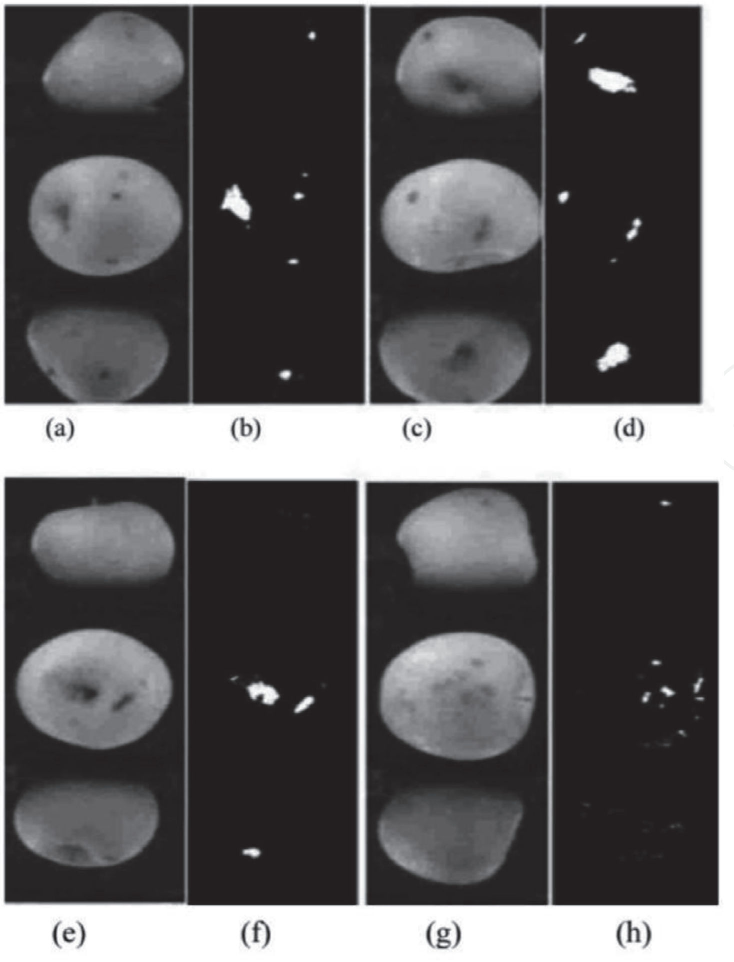


Figure 26.
Defects segmentation results. (a), (c), (e), and (g) original image; (b), (d), (f), and (h) segmented defects [6].

Forty samples of Fuji apples were used to test and validate the system. **Figure 26** illustrates how the input apple image is segmented and the defected regions as well as the stem and calyx defects are detected. The neural network classifier to be very effective in detecting stem-calyx recognition with accuracies over 93% [6]. Overall, this system proved to be successful in detecting defects on multiple sides of an apple simultaneously, while on a sorting line.

Xing [19] also implemented a non-destructive automated technique to detect bruises on apples using multiple waveband techniques. Hyperspectral imaging can provide enough information in several wavebands, but it is inappropriate in an on-line system due to its long acquisition and analysis time. Instead, Xing [19] resided on using multi-spectral imaging where only a specific range of wavebands was used to detect apple bruises.

A total of 128 'Golden Delicious' apples were purchased from two different locations and separated into non-bruised and bruised groups by visual inspection. Bruises are usually caused by human handling and vibration from transportation. Apples without visible bruises were impacted with a pendulum in the laboratory to achieve an average bruise size of 17 mm in diameter [19]. The hyperspectral imaging system consisted of a conveyor belt, light source, and camera for on-line bruise detection of apples as shown in **Figure 27**. The camera has high sensitivity from 400 to 1000 nm and is used alongside a spectrograph to detect the separate wavebands of light. The system also consisted of light sources and operated under a controlled environment to minimize interference from ambient light.

A simple thresholding method was used to segment the image background and low-intensity regions and further analyzed by principal component analysis (PCA).

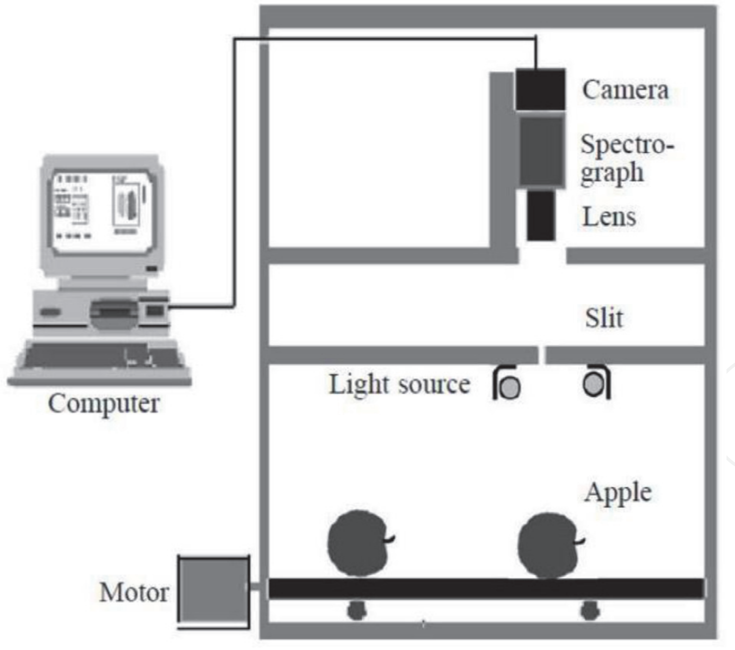


Figure 27.
Schematic of the used hyperspectral imaging system [19].

PCA is an effective tool in reducing data dimensionality and to enhance bruise features. Results showed that the wavebands centered at 558, 678, 728, and 892 nm were optimal in detecting bruises on 'Golden Delicious' apples. A simple classification technique was introduced to determine whether apples are bruised or intact. This classification technique resulted in an accuracy of 93.5% for detecting intact apples and about 86% for detecting bruised apples.

4. Conclusion

Both preharvest and postharvest imaging and VOC profiling techniques have proven to be very effective inaccurately classifying different types of plant diseases. Not only do these techniques give a good indication of overall plant health but also can accurately distinguish healthy produce from unhealthy produce. Preharvest techniques such as [18, 20] achieved a classification accuracy of plant diseases of 82.5% and 90% respectively. Postharvest techniques showed to be more promising as seen in [6, 22] with a classification accuracy of fruit defects of 89.2% and 93% respectively. Preharvest disease detection techniques can be classified as an early disease detection method as seen in [8, 18], in which immediate action can be taken to revive plants and crops. This aspect is a major advantage and cannot be achieved with postharvest techniques. Postharvest techniques such as [6, 19] have introduced automated systems in which defected postharvest produce can be distinguished and sorted automatically with an accuracy of 93% and 86% respectively. However, the integration of automation under real-time and field-based environments is still very limited.

As seen in [8], a robot rig is used under field-based conditions to detect diseases in grapevine canopy but is controlled manually and full automation is not achieved. Also, [21] implemented a semi-autonomous robot to test soil fertility under field-based environments using multiple gas sensors, but results were ineffective in disease detection.

The methods discussed differ greatly, from the use of simple digital cameras to the use of more advanced and sophisticated hyperspectral and multispectral imaging methods. Techniques such as [6, 19, 22] that use multispectral cameras and bandpass filters, show higher classification accuracy as seen in **Table 5** when compared to other techniques that use simple digital cameras for image capture. The use of multispectral cameras provides more information on the image that can be used to extract defected or diseased areas which may not be clear when using simple digital cameras that have low sensitivity in the higher wavebands [19]. indicated that higher wavebands were helpful in detecting bruises in apples, and this cannot be achieved when using a simple digital camera.

A. Key Achievements

- Plant nutrient deficiencies can be detected at a very early stage for fast and appropriate actions to be taken as shown in [18].
- Automated robotic selective pesticide spraying is achieved with adequate accuracy as shown in [8].
- The use of e-nose sensors and VOC profiling give farmers good indications on land and soil fertility as shown in [21].
- Automated sorting of fruits with very high accuracy is achieved as shown in [6, 19].

B. Challenges with Preharvest techniques

- Images of leaves are taken off the field and in controlled environments as shown in [7, 17, 18, 20].
- Automation techniques and the use of agriculture robots are not fully developed and achieve varying results as shown in [8, 21].
- Limited applications for processing large numbers of plants in real-time under field conditions.

C. Challenges with Postharvest techniques

- Tests are not field-based and conducted under controlled environments as shown with [1, 2, 6].
- Postharvest techniques are classified as late disease detection methods. It is difficult to cure the disease after the fruit has been fully developed.

5. Future work

After reviewing the research, multispectral and hyperspectral imaging techniques proved to be the most reliable indirect method. However, hyperspectral imaging is very costly, and there is still a limitation in the capability of designing systems for the detection of diseases in real-time under field conditions. Most preharvest and postharvest techniques are completed under controlled environments as seen in **Table 4** and automation techniques are developed mainly for postharvest produce for fruit sorting as seen in **Table 5**. Because the use of preharvest techniques provides an early analysis of disease severity, preharvest is more suitable to use over postharvest techniques.

Paper	Acquisition Method	Test Plant	Target Disease	Environment	Automation/ Manual	Coverage Area	Segmentation Method	Classifier	Accuracy
Patil [13]	12 Mega Pixel Digital Camera	Sugarcane leaves	Fungi diseases	Off-Site Controlled Background	Images Taken Manually	Single leaf	Triangle Thresholding	NA	98%
Li [9]	10 Mega pixel Digital Camera	Pomegranate leaves	General disease spots	Off-Site Controlled Background	Images Taken Manually	Single leaf	K-means clustering	Fuzzy Logic Classification	High
Xu [19]	Digital Camera with 0.4 million CCD pixels	Tomato plants	Nutrient deficiency	Closed Chamber	Images Taken Manually	Single leaf	Percent Histogram	Fuzzy k nearest neighbor classifier	82.50%
Camargo [4]	24 bit JPEG Image samples	Cotton Crop	Green stink bug, Bacteria angular, Ascochyta blight virus	Off-Site	Images Taken Manually	Single leaf	Co-occurrence matrix	Support Vector Machine Classifier	90%
Oberti [12]	Three-CCD Multispectral Camera 1912x1076	Grapevines	Powdery mildew	On-Site Controlled Lighting	Robot Rig Limited automation	Grapevine canopy	NDVI calculation	Local Gradient Method	85%
Pobkrut [15]	Multiple Gas Sensors (e-nose)	Soil fertility	VOCs	On-Site	Semi-autonomous six-wheel robot	Lawn	NA	NA	NA

Table 4.
Review of preharvest disease detection techniques.

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Paper	Acquisition Method	Test Fruit	Target Disease	Environment	Automation/ Manual	Coverage Area	Segmentation Method	Classifier	Accuracy
Jhuria [7]	Apple Image dataset	Apples	Apple scab and Apple rot	Off-Site Controlled Background and Lighting	Images Taken Manually	Single fruit	Color and Texture Extraction	Neural Network	High
Dubey [6]	Apple Image dataset	Apples	Apple blotch, rot, and scab	Off-Site Controlled Background and Lighting	Images Taken Manually	Single fruit	K-means segmentation	Support Vector Machine	High
Unay [18]	Monochrome Digital Camera with multiple bandpass filters	Jonagold Apples	Skin defects, bruises, and rot	Off-Site Controlled Background and Lighting	Images Taken Manually	Single fruit	Isodata Thresholding	Support Vector Machine	89.20%
Li [9]	2 Monochrome cameras with a bandpass filter	Apples	Surface defects	Off-Site Closed Chamber	Full automation	Multiple fruits	Simple subtraction thresholding	Neural Network	93%
Xing [22]	Multispectral Camera (400-1000 nm)	Golden Delicious Apples	Apple bruises	Off-Site Closed Chamber	Full automation	Multiple fruits	Simple thresholding	Principal Component Analysis	86%

Table 5.
Review of postharvest disease detection techniques.

For a reliable, rapid, and field-based disease detection system, a new preharvest automated method is required. A fusion of techniques such as VOC profiling and NIR imaging methods could be integrated into a robot for processing a large number of plants. Because of the uncertainty of lighting and other conditions of the field environment more advanced tools are required to capture data without being affected. An agriculture robot can be designed to move in agriculture fields to detect stresses in areas while providing position information. RGB and NIR imaging methods could be integrated into a robot and used in synchronization to measure overall plant health using the Normalized Differential Vegetative Index (NDVI). Because of its low cost, NIR imaging techniques can be very efficient and effective when integrated with a robot. The detection of stressful areas in a field with GPS information can be used for selective pesticide spraying.

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References

[1] M. Jhuria, A. Kumar, and R. Borse, "Image processing for smart farming: Detection of disease and fruit grading," in 2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013), Dec. 2013, pp. 521–526, doi: 10.1109/ICIIP.2013.6707647.

[2] S. R. Dubey and A. S. Jalal, "Detection and Classification of Apple Fruit Diseases Using Complete Local Binary Patterns," in 2012 Third International Conference on Computer and Communication Technology, 2012, pp. 346–351, doi: 10.1109/ICCCT.2012.76.

[3] D. Pimentel, R. Zuniga, and D. Morrison, "Update on the environmental and economic costs associated with alien-invasive species in the United States," Ecol. Econ., vol. 52, no. 3, pp. 273–288, Feb. 2005, doi: 10.1016/j.ecolecon.2004.10.002.

[4] S. Sankaran, A. Mishra, R. Ehsani, and C. Davis, "A review of advanced techniques for detecting plant diseases," Comput. Electron. Agric., vol. 72, no. 1, pp. 1–13, Jun. 2010, doi: 10.1016/j.compag.2010.02.007.

[5] M. López *et al.*, "Innovative tools for detection of plant pathogenic viruses and bacteria," Int. Microbiol. Off. J. Span. Soc. Microbiol., vol. 6, pp. 233–243, Jan. 2004, doi: 10.1007/s10123-003-0143-y.

[6] Q. Li, M. Wang, and W. Gu, "Computer vision based system for apple surface defect detection," Comput. Electron. Agric., vol. 36, no. 2, pp. 215–223, Nov. 2002, doi: 10.1016/S0168-1699(02)00093-5.

[7] S. Sannakki, V. Rajpurohit, V. Nargund, A. Kumar, and P. Yallur, "Leaf Disease Grading by Machine Vision and Fuzzy Logic," Int J, vol. 2, Nov. 2010.

[8] R. Oberti, M. Marchi, P. Tirelli, A. Calcante, M. Iriti, and E. Sciences-DiSAA, "The CROPS agricultural robot: application to selective spraying of grapevine's diseases," p. 8.

[9] B. Alberts, A. Johnson, J. Lewis, M. Raff, K. Roberts, and P. Walter, "General Principles of Cell Communication," Mol. Biol. Cell 4th Ed., 2002. Available: https://www.ncbi.nlm.nih.gov/books/NBK26813/ [Accessed: Nov. 09, 2020].

[10] J. J. Belasque, M. C. G. Gasparoto, and L. G. Marcassa, "Detection of mechanical and disease stresses in citrus plants by fluorescence spectroscopy," Appl. Opt., vol. 47, no. 11, pp. 1922–1926, Apr. 2008, doi: 10.1364/AO.47.001922.

[11] E. C. Lins, J. Belasque, and L. G. Marcassa, "Detection of citrus canker in citrus plants using laser induced fluorescence spectroscopy," Precis. Agric., vol. 10, no. 4, pp. 319–330, Aug. 2009, doi: 10.1007/s11119-009-9124-2.

[12] J. West, C. Bravo, R. Oberti, D. Lemaire, D. Moshou, and H. McCartney, "The Potential of Optical Canopy Measurement for Targeted Control of Field Crop Diseases," Annu. Rev. Phytopathol., vol. 41, pp. 593–614, Feb. 2003, doi: 10.1146/annurev.phyto.41.121702.103726.

[13] S. Lenk *et al.*, "Multispectral fluorescence and reflectance imaging at the leaf level and its possible applications," J. Exp. Bot., vol. 58, no. 4, pp. 807–814, Mar. 2007, doi: 10.1093/jxb/erl207.

[14] C. Bravo, D. Moshou, J. West, A. McCartney, and H. Ramon, "Early Disease Detection in Wheat Fields using Spectral Reflectance," Biosyst. Eng., vol. 84, no. 2, pp. 137–145, Feb. 2003, doi: 10.1016/S1537-5110(02)00269-6.

[15] A. Vallat, H. Gu, and S. Dorn, "How rainfall, relative humidity and temperature influence volatile emissions from apple trees in situ," Phytochemistry, vol. 66, no. 13, pp. 1540–1550, Jul. 2005, doi: 10.1016/j.phytochem.2005.04.038.

[16] J. M. Cevallos-Cevallos, R. Rouseff, and J. I. Reyes-De-Corcuera, "Untargeted metabolite analysis of healthy and Huanglongbing-infected orange leaves by CE-DAD," Electrophoresis, vol. 30, no. 7, pp. 1240–1247, Apr. 2009, doi: 10.1002/elps.200800594.

[17] S. B. Patil and D. S. K. Bodhe, "Leaf disease severity measurement using image processing," p. 6, 2011.

[18] G. Xu, F. Zhang, S. G. Shah, Y. Ye, and H. Mao, "Use of leaf color images to identify nitrogen and potassium deficient tomatoes," Pattern Recognit. Lett., vol. 32, no. 11, pp. 1584–1590, Aug. 2011, doi: 10.1016/j.patrec.2011.04.020.

[19] J. Xing, C. Bravo, P. T. Jancsók, H. Ramon, and J. De Baerdemaeker, "Detecting Bruises on 'Golden Delicious' Apples using Hyperspectral Imaging with Multiple Wavebands," Biosyst. Eng., vol. 90, no. 1, pp. 27–36, Jan. 2005, doi: 10.1016/j.biosystemseng.2004.08.002.

[20] A. Camargo and J. Smith, "Image pattern classification for the identification of disease causing agents in plants," Comput. Electron. Agric., vol. 66, pp. 121–125, May 2009, doi: 10.1016/j.compag.2009.01.003.

[21] T. Pobkrut and T. Kerdcharoen, "Soil sensing survey robots based on electronic nose," in 2014 14th International Conference on Control, Automation and Systems (ICCAS 2014), Oct. 2014, pp. 1604–1609, doi: 10.1109/ICCAS.2014.6987829.

[22] D. Unay and B. Gosselin, "Thresholding-based segmentation and apple grading by machine vision," Jan. 2005.